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Original Research

Optimization of Sustainable-Robust Biofuel Supply Chain under Uncertainty

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Abstract

The increased knowledge about environment and decline in reservoirs of fossil resources has led the industry to enhance and produce other sustainable fuels by using renewable, which are environmentally acceptable. Biofuel is a kind of fuel derived from biomass resources. Biomass is also the source of fossil fuels that are used today; however, this biomass has been formed over long years. The reduction in fossil fuel resources and the destructive effect of these fuels on the environment have made researchers replace such resources. Therefore, the extant study presented a multi-objective mathematical model for a biofuel sustainable supply chain, by consideration of demand uncertainty. Finally, the research developed the mathematical model considering uncertainty and using Bertsimas and Sim Robustness Approach. According to the proposed model, sustainability objectives were discussed and investigated, including economic, social, and environmental issues. Ultimately, the presented model was confirmed by using the epsilon constrained method (ε constrained method) and the model was validated using the integrated ε constrained-Benders Approach.

Keywords: Biofuel, Biomass, Sustainable-Robust, Supply Chain.

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Introduction

The most critical issue that threatens the energy supply for developing countries is severe dependence on rare oil resources. Among different types of renewables, the production of green fuels (biofuels) has received great importance and attention in different parts of the world over recent years (Kumar et al., 2019). Many resources have been used to produce biofuels, which have been classified into several generations over past years (Maity et al., 2014). The first generation includes materials of nutritional nature, such as corn, soybeans, and starch. Although it is cost-effective to produce fuel by using such materials, these materials have been gradually eliminated due to the high price of foodstuff (Babazadeh et al., 2015). The second generation comprises materials that do not have nutritional value, such as agricultural waste, including corn husks, products used for energy production like Jatropha, and industrial waste. Microalgae-based fuel production has been named the third generation due to its different production nature (Mohseni et al., 2016). The integrated management and coordination of production cycles is one of the crucial issues considered in the development of biofuels at the macro scale (Scaldaferri & Pasa, 2019). Hence, it is essential to develop some supply chain design models that can control all phases from feedstock supply to fuel production and supply within an integrated framework (Yue et al., 2014). A supply chain comprises all facilities, tasks, and activities involved in the production and delivery of a product or service, from suppliers (and their suppliers) to customers (and their customers). The supply chain also includes demand-supply planning and management, production and scheduling of a product or service, warehousing, inventory control and distribution, delivery, and customer service. Supply chains exist in manufacturing and service organizations; however, supply chain complexity may severely vary in different industries and companies (Ahmadi et al., 2018). The supply chain is an integration process among suppliers, producers, and distributors in every organization. This integrated process aims to fulfill the organization's policies, minimize circulating inventory, and meet the demand of each customer at the end of the supply chain (Nugroho & Zhu, 2019). To balance and manage the production process of each phase in the supply chain procedure, each input and output value of warehouses must be controlled, and then inputs and outputs of each operational phase should be estimated by defining correlated variables. In general, the supply chain is defined as a process that covers all activities related to commodity flow and materials conversion, from the preparation of raw material to the delivery of the final product to the consumer. Supply chain management integrates supply chain activities with their associated information flows by improving chain relations to achieve a permanent and reliable competitive advantage (Albashabsheh & Stamm, 2019). Urban waste has received great attention as one of the sources for the production of second-generation biofuels over recent years (Ye et al., 2018). Hence, supply chain design can be used for macro scale planning to produce fuel from urban waste. A problem-solving approach is one of the most critical concerns and issues in the design and optimization of the supply chain. The reason is that network design models are usually categorized into complex problems. Therefore, those samples of biofuel supply chain models with small dimensions can be solved by using exact methods. On contrary, there is uncertainty- due to complexity-in basic parameters of the mathematical model in the real world’s problems, which have been neglected in studies in this scope (Chibeles-Martins et al., 2016). To solve this problem, therefore, the present study selects the problem by using a robustness approach, which

has led to considerable innovation in this context. On the other hand, supply chain management is a multi-objective decision-making problem that occurs under the supervision of experts and under real conditions. Therefore, it is necessary to develop a multi-objective mathematical model for the concept of a biofuel supply chain. As a result, the extant study presents a multi-objective mathematical model for sustainable biofuels' supply chain by consideration of demand uncertainty. Ultimately, this paper develops the mathematical model by paying attention to the considered uncertainty and using Bertsimas and Sim Robustness Approach. In the last step, this study uses the ε constrained method to evaluate the multi-objective and Benders Approach through GAMS software and CPLEX solver.

Research Background

Over extraction of coal, natural gas, and oil resources has accelerated the destruction of these resources, fuel price oscillation, and unsustainable energy supply. Moreover, energy consumption has increased, especially in industrial countries due to population growth, lifestyle changes, and higher living standards (Max & Johnson, 2019). Hence, the European Commission has set the 20% use of energy production from a renewable resource for EU members up to 2020. Furthermore, greenhouse gases must experience a 20% reduction up to 2020 compared to 1990. Although each member state has defined its goal, biomass plays a key role in new renewables due to the homogeneity and extensive distribution of this biomass all around the world(Ba et al., 2016; Frombo, Minciardi, Robba, & Sacile, 2009; Frombo, Minciardi, Robba, Rosso, et al., 2009; Kanzian et al., 2013) This energy resource provides some advantages in different fields, including environmental pollution, energy diversity and security, and economy (Long et al., 2013; Mobini et al., 2011). Green fuel is a broad term, which comprises some resources: trees, crops, industrial organic algae, human and animal wastes, etc. (Frombo, Minciardi, Robba, & Sacile, 2009; Mafakheri & Nasiri, 2014). In particular, it is possible to use forest biomass for a wide range of uses of generating heat, power, fuel, and chemicals (Cambero & Sowlati, 2014; Rentizelas et al., 2009). In addition, we can save and use this energy resource to produce energy and meet the energy demand, which is a relative advantage of this resource compared to other renewables (Rentizelas et al., 2009; Shabani et al., 2013). Biofuel deals with several problems in its supply chain besides the capabilities mentioned above. For instance, high costs caused by geographical dispersion of resources, variation in quality and available volumes, lower energy density rather than fossil fuels, and heterogeneity of multi-corporate structure can be mentioned as challenges existing in the supply chain of biofuels (Cambero & Sowlati, 2014; Kanzian et al., 2013; Rentizelas et al., 2009; Shabani et al., 2013). According to the mentioned issues, logistic costs indicate the continuous increasing use of forest biomass for energy production. Therefore, we must optimize the supply chain in a way to make it more efficient and competitive (Cambero & Sowlati, 2014; De Meyer et al., 2014; Flisberg et al., 2012). Biomass supply chain management is usually divided into three strategic, tactical, and operational levels (Ba et al., 2016; Lin et al., 2014). Strategic decisions are made regarding long-term decision-making. Strategic decisions also evaluate biomass resources and industries pertained to the customer, location, size, and design of these industries (Lin et al., 2014). On the other hand, tactical planning addresses midterm and short-term decisions, such as production, delivery, and biomass process programs. Ultimately, the operational phase discusses

short-term decisions about the intra-field operations from biomass collection and conversion (converting biomass to energy) (Frombo, Minciardi, Robba, & Sacile, 2009; Lin et al., 2014). Babazadeh et al. (2015) argues that the rapid expansion of first-generation biodiesel production from vegetable oils and animal fats has made the development policymakers and experts worried about the allocation of agricultural lands, foodstuff supply, and balance of the food market. In this regard, second-generation biofuel manufactured from inedible feedstock has provided many advantages over recent years. It is necessary to optimize and design the whole biofuel supply chain systematically to accelerate vital biofuel transfer at a large and cons-effective scale. Mirhashemi et al. (2018) presented a two-phase optimization model to design a biological biomass-based biofuel. The first phase considered a Common Weight Data Envelopment Analysis (CWDEA) to rack production farm locations, while the second phase proposed mixed-integer linear programming to find optimum production levels in the strategic and tactical supply chain. Soares et al. (2019) proposed a mixed linear programming model to support the decision made in the initial timeframe, which led to the development of the fuel supply chain. Other studies addressed the developed modeling and optimization of the supply chain (De Meyer et al., 2014; Mafakheri & Nasiri, 2014; Shabani et al., 2013). Habib et al. (2021) presented a robust possibility programming (RPP) approach to the animal fat-based biodiesel supply chain by considering uncertainty in the problem's parameters. They formulated the model by using a mixed-integer programming approach. The objective function is supposed to minimize total construction costs, purchase costs, operations costs, and transportation costs, also the costs pertained to the tax on pollutants emitted by the manufacturing setting. It should be mentioned that a tax rate was considered for CO_2 emission and other pollutants to cover the environmental indicators. The mentioned tax was taken into account in addition to other costs in the objective function of the problem. Moreover, some parameters of the model were considered using the fuzzy approach to deal with parameters' uncertainty. Next, the RPP approach was used to solve the model, and then a case study of Pakistan was proposed. The results obtained from this study indicated the efficiency of the solution approach in real-world dimensions. Yadala et al. (2020) optimized the algal biomass supply chain to biodiesel. It is a common approach to convert algal biomass into biodiesel for biodiesel production. Yadala et al. (2020) formulated this chain by using a single-objective mixed-integer programming model. The objective was to minimize the overall cost of the network, which included production, operation, and transportation costs over a planning horizon of ten years. Kang et al. (2020) suggested a three-stage design for an algae-based biofuel supply chain using a geographic information system (GIS). To do this, they proposed a single-objective mixed-integer programming model. The objective function of this model minimized the total cost of the supply chain, which included costs of transportation, production, and greenhouse gases emission resulting from supply chain activities. Zheng et al. (2020) investigated the role of government policies in making the waste cooking oil-to-biodiesel systems more efficient. In this lieu, they describe various policies and strategies used to make the supply chain more efficient and sustainable. Next, they presented a collaborative game to address these strategies. Mohseni and Pishvaee (2020) designed a robust optimization model for the waste-to-biodiesel supply chain. They used the data-based robust optimization approach to overcome uncertainty in the parameters of the model. Moreover, they employed a fuzzy neighborhood support system of data samples to reduce dependency on the background data. The objective

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function minimized costs of the supply chain, which included costs of setting deployment, costs of the pipeline, operational costs, production costs, and transportation costs. According to the results of reviewed papers, most papers have been conducted at the strategic level in which, supply chain design has been at the center of attention. However, sourcing, supply contracts, and environmental discussions have been neglected at this level. Most reviewed papers have considered the exact state, and there is a literature gap in probabilistic and mixed discussions. However, consideration of uncertainty in climate issues and production of crops is one critical discussion in the biofuel supply chain especially those with agricultural and forest sources. The majority of studies have considered some objective functions, such as profit and cost, while other objective functions, including minimization of greenhouse gases and maximization of the number of jobs that consider sustainability and environmental issues have been ignored (Sarker et al., 2019) The reviewed papers conducted on the biofuel supply chain were classified as shown in Table 1.

Table 1. Evaluation of studies conducted on biofuel supply chain

Author/year	Objectives	Multi-period	Multi-objective	Sustainability	Uncertainty	Uncertainty parameter
Mol et al. (1997)	8					
Nagel (2000)	1					
Tembo et al. (2003)	3	*				
Freppaz et al. (2004)	1					
Gunnarsson et al. (2004)	3	*				
Mapemba et al. (2007)	3	*				
Dunnett et al. (2007)	1	*				
Mapemba et al. (2008)	3	*				
Vlachos et al. (2008)	1					
Frombo, Minciardi, Robba, Rosso, et al. (2009)	1					
Zamboni et al. (2009)	1		*			
Ekşioğlu et al. (2009)	1	*				
Huang et al. (2010)	1	*				
Akgul et al. (2011)	1					
Kim et al. (2010)	2					
Dal-Mas et al. (2011)	3	*			*	Biofuel cost
Zhu et al. (2011)	2	*				
Marvin et al. (2012)	3					
An et al. (2011)	2	*				
You et al. (2012)	7	*	*	*		
You and Wang (2011)	7	*	*			
Lam et al. (2011)	2					
Zhu & Yao (2011)	2					
Kim et al. (2011)	2				*	Supply values, market demand, market prices
Chen and Fan (2012)	1				*	Feedstock supply,

Author/year	Objectives	Multi-period	Multi-objective	Sustainability	Uncertainty	Uncertainty parameter
						biofuel demand
Balaman and Selim (2014)	2					
Giarola et al. (2013)	3	*	*		*	feedstock, cost fluctuations of carbon trades
Paolucci et al. (2016)	3	*	*			
Roni et al. (2017)	7		*	*		
Azadeh and Arani (2016)	2	*			*	Available biofuel, demand
Duarte et al. (2016)	2	*				
De Meyer et al. (2016)	11	*				
Miret et al. (2016)	10	*	*	*		
Ng and Maravelias (2017)	1	*				
Cambero et al. (2016)	3	*	*			
Cambero & Sowlati (2014)	3	*	*	*		
Mirhashemi et al. (2018)	2	*		*		
Sarker et al. (2019)	3	*	*	*		
Foo (2019)	3	*	*			

The research gap in reviewed studies was non-consideration of sustainability in the biofuel supply chain. Most studies have addressed cost minimization and profit maximization. Robustness of supply chain models was not used, which was another research gap. However, some studies examined a scenario to eliminate uncertainty, which was an efficient approach due to its inapplicability. Therefore, the present study aims to design a biofuel production supply chain, and develop it by minimizing social issues, costs of pollutants, and risk.

Research Methodology

The present study aims to solve the problem of programming the supply chain pertained to biofuels by considering uncertainty in the parameters of the model. The extant supply chain involves three levels of biomass supply, refineries, and supply centers. Refineries purchase the feed stocks required for biofuel production from different biomass suppliers based on the available technology of the refinery. They transfer the feedstock to the refinery by considering the access of the transportation facility, and then convert it to the end product (i.e., biofuel) through a specific process. The transportation facility is chosen based on the distance between biomass supply centers, refineries, and fuel supply centers, as well as the volume of hazardous gases emitted by each transportation option. These considerations are taken into account to minimize costs, reduce pollutants, and increase social welfare.

Assumptions of the problem have been described herein:

- The supply chain is composed of several biomass suppliers, biorefineries, and demand centers

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- Refineries have access to transportation facilities to supply biomass and end-product
- Refineries can produce the fuel based on the available technology
- It is possible to produce fuel in refineries based on the available technology
- The cost of inventory maintenance and lost sales are accounted for in producers' expenses
- The demand for the end product is a function of the price
- The planning horizon of several periods is considered
- The initial inventory is given for the feedstock (or raw materials) and end product (final or finished product) in refineries
- Fuel is processed in refineries and demand locations sell the fuel
- The available transportation facilities have been considered equally in all supply chain layers
- Each transportation option has a default rate of hazardous gas production
- The supply risk component is evaluated in a certain space of the model

the extant study has been structured based on the paper published by Mirhashemi et al. (2018) and Nur et al. (2021) egarding the studied problem of study. Production and sustainability were also added to the considered problem. We have the following variables to model the problem.

Set of indicators

Set of biomass types that are indicated with i	I
Set of biomass area type I	J_i
set of potential locations for refineries	F
set of biofuel types	E
set of consumption markets	M
Set of time stages indexed by t	T
Set of technologies used in refinery f indexed by r	R_f
Set of scenarios	S
Set of transportation facilities	K

Set of parameters

Cost of purchasing urban waste biomass type i	pr_i
Cost of producing urban waste biofuel type e by using technology type r	C_{er}
The average velocity of facility type k	V_k
The fixed capital cost of annual refinery set up in location f using technology r	f^F_{fr}

The annual capital cost of each refinery unit placed in location f using technology r to produce fuel e	f^{V}_{efr}
The distance between nodes x and y	d_{XY}
Solid volumes' distance-dependent shipment cost, such as transport cost of bulk facility per mile, which includes fuel, insurance, repair, and maintenance costs	t^{d}_{bk}
Solid volumes' transfer time-dependent shipment cost, such as the one-hour transport cost of each bulk facility, which includes wages (paid to workers) and capital costs	t^{t}_{bk}
The shipment cost depends on the distance of solid volumes shipped by facility k	t^{d}_{lqk}
The shipment cost depends on the transport time of solid volumes shipped by facility k	t^{t}_{lqk}
Cost of loading and unloading facility k for solid volumes	lu_{bk}
Cost of loading and unloading facility k for liquid volumes	lu_{lqk}
Cost of inventory control for biofuel e in city m	α_{em}
Cost of biofuel e shortage in city m	$_{em}\beta$
Solid volume capacity of facility k	Cap_{bk}
Liquid volume capacity of facility k	Cap_{lqk}
The moisture content of biomass i	Mc_{i}
Biomass shipment cost coefficient by facility k from biomass areas to refineries (1) $$CC^{1}_{ijifk} = \left(\left(t^{d}_{bk} + \frac{t^{t}_{bk}}{V_k}\right) * \frac{d_{jif}}{Cap_{bk}} + lu_{bk}\right) 1/(1 - MC_i)$$	CC^{1}_{ijifk}
Shipment cost coefficient of biofuel from refineries to demand centers (2) $$CC^{2}_{efmk} = \left(\left(t^{d}_{lqk} + \frac{t^{t}_{lqk}}{V_k}\right) * \frac{d_{fm}}{Cap_{lqk}} + lu_{lqk}\right)$$	CC^{2}_{efmk}
The conversion rate of refinery: measuring the amount of biofuel e that can be produced by one ton of dried biomass i using technology r	η_{ier}
Maximum allowed capacity of the refinery in location f using technology r for biofuel e	$Capr_{efr}$
The capacity of biofuel e stored in city m	$Capi_{em}$

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Maximum available biomass i in the area j_i at the time phase t under the scenario s	S^t_{jis}
The demand in city m at phase t for biofuel e under the scenario s	D^t_{ems}
Binary parameter equals 1 when the connection between area j_i and biomass in the refinery is usable in the location f under the scenario s	x^t_{jifs}
The binary parameter equals 1 if the interface between refinery and city m is useable in location f under the scenario s	t^t_{fms}
The binary parameter equals 1 if the area j_i of biomass has access to facility k in time phase t	${}^t_{kji}\Upsilon$
The binary parameter equals 1 if refinery f has access to facility k in time phase t	λ^t_{kf}
Probability of scenario s	$Prob_s$
NO_2 emission rate in distance unit for transportation of vehicle k	G_N^k
CO emission rate in distance unit for transportation of vehicle k	G_c^k
Number of jobs created in refinery center f with technology r in time t	A_{fr}^t
Number of accidents occurred in refinery center f with technology r in time t	B_{fr}^t
Risk of supplying biomass i from supplier j in time t	RY^t_{ji}
Set of decision variables	
The volume of biomass i purchased from the j_i area in time phase t under the scenario s	Y^t_{jis}
The volume of biomass i transported from j_i area to refinery f by facility K in time phase t under the scenario s	X^t_{jifsK}
The volume of biofuel e transported from refinery f to city m by the facility K in time phase t under the scenario s	y^t_{efmsK}
The capacity of the refinery f designed by technology r for biofuel e in time phase t under the scenario s	Cap^t_{efrs}
The available volume of biofuel e in city m in time phase t under the scenario s	I^t_{ems}
Shortage of biofuel e in city m in time phase t under the scenario s	q^t_{ems}
Amount of biofuel e produced in refinery f in time phase t under the scenario s	$Prod^t_{efs}$
It equals 1 if refinery f with technology r works in time phase t under the scenario s	Z^t_{frs}

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Mathematical Modelling

The mathematical model of the problem is expressed by considering of parameters set and variables of the problem:

(3) Min cost $= \sum_{s\in S}\sum_{t\in T} prob_s \{\sum_{f\in F}\sum_{r\in R_f}(f^F{}_{fr}\, Z^t{}_{frs} + \sum_{e\in E}(f^V{}_{efr}\, cap^t{}_{efrs})) + \sum_{i\in I}\sum_{j_i\in J_I} pr_i\, Y^t{}_{jis} + \sum_{e\in E}\sum_{r\in R_f}\sum_{f\in F} C_{er}\, prod^t{}_{efs} + \sum_{i\in I}\sum_{j_i\in J_I}\sum_{f\in F}\sum_{k\in K} CC^1{}_{ijifk}\, X^t{}_{jifsk} + \sum_{e\in E}\sum_{f\in F}\sum_{m\in M}\sum_{K\in k} CC^2{}_{efmk}\, y^t{}_{efmsk} + \sum_{e\in E}\sum_{m\in M}(\alpha_{em}\, I^t{}_{ems} + \beta_{em}\, q^t{}_{ems})\}$

(4)

$$Min\ pollutants = \sum_{s\in S}\sum_{t\in T} prob_s \ \{\sum_{j_i\in J_I}\sum_{f\in F}\sum_{k\in K} X^t{}_{jifsk} G_N^k\, d_{jif} + \sum_{e\in E}\sum_{f\in F}\sum_{k\in K}\sum_{m\in M} y^t{}_{efmsk} G_N^k\, d_{fm} + \sum_{j_i\in J_I}\sum_{f\in F}\sum_{k\in K} X^t{}_{jifsk} G_C^k d_{jif} + \sum_{e\in E}\sum_{f\in F}\sum_{k\in K}\sum_{m\in M} y^t{}_{efmsk} G_C^k\, d_{fm}\}$$

(5)

$$Min\ Risk = \sum_{s\in S}\sum_{t\in T} prob_s \left\{\sum_{j_i\in J_I}\sum_{f\in F}\sum_{k\in K} \mathrm{Y_{tjis}} * \mathrm{RY_{tji}}\right\}$$

$$Maxwelfare = prob_s \left\{\sum_{t\in T}\sum_{s\in S}\sum_{f\in F}\sum_{r\in R_f}\left(A^t_{frs} - B^t_{frs}\right) Z^t_{frs}\right\}$$

$$\sum_{e\in E} Cap^t{}_{efrs} \le \sum_{e\in E} capr_{efr}\, Z^t{}_{frs} \qquad \forall\, f\in F, s\in S, t\in T, r\in R_f$$

(6)

$$prod^t{}_{efs} \le cap^t{}_{efrs} \qquad \forall\, e\in E, f\in F, s\in S, t\in T$$

(7)

$$I^t{}_{ems} \le capi_{em} \qquad \forall\, e\in E, m\in M, s\in S, t\in T$$

(8)

$$\sum_{j_i \in J_I} \sum_{i \in I} \sum_{k \in K} X^t{}_{jifsk}\, \eta_{ier} = prod^t{}_{efs} \quad \forall\, e \in E, f \in F, s \in S, t \in T, r \in R_f$$

(9)

$$\sum_{m \in M} \sum_{k \in K} y^t{}_{efmsk} = prod^t{}_{efs} \qquad \forall e \in E, f \in F, s \in S, t \in T$$

(10)

$$\mathrm{Y}^t{}_{\mathrm{jis}} = \sum_{f \in F} \sum_{k \in K} X^t{}_{jifsk} \qquad \forall j_i \in J_I, s \in S, t \in T$$

(11)

$$Y^t{}_{jis} \le S^t{}_{jis} \qquad \forall j_i \in J_I, s \in S, t \in T$$

(12)

$$\sum_{f \in F} \sum_{k \in K} y^t{}_{efmsk} + q^t{}_{ems} + I^{t_1}{}_{ems} - I^t{}_{ems} = D^t{}_{ems}(p^t{}_{ems}) \qquad \forall e \in E, m \in M, s \in S, t \in T$$

(13)

$$\sum_{r \in R_f} Z^t{}_{frs} \le 1 \qquad \forall f \in F, s \in S, t \in T$$

(14)

$$\sum_{k \in K} y^t{}_{efmsk} \le t^t{}_{fms} M \qquad \forall e \in E, f \in F, m \in M, s \in S, t \in T$$

(15)

$$\sum_{k \in K} X^t{}_{jifsk} \le x^t{}_{jifs}\, M \qquad \forall j_i \in J_I, f \in F, s \in S, t \in T$$

(16)

$$\sum_{f \in F} \sum_{s \in S} X^t{}_{jifsk} \le \Upsilon_{kji\,t}\, M \qquad \forall j_i \in J_I, k \in K, t \in T$$

(17)

$$\sum_{e\in E}\sum_{m\in M}\sum_{s\in S} {y^t}_{efmsk} \leq \lambda_{kft}\, M \qquad \forall\ f \in F, k \in K, t \in T$$

Model Description

According to the proposed model, equation (3) represents the economic objective function that minimizes the total costs of the chain. Equation (4) indicates the second objective function (environmental) that minimizes the emission of hazardous gases, including NO_2 and CO. Equation (4) also comprises the third objective function that minimizes social performance of a sustainable supply chain, which considers job creation and the number of accidents occurred in active refineries per period and scenario. Equation (5) minimizes the risk of biomass supply. Equations (6), (7), and (8) represent the capacity constraints. Firstly, these constraints indicate that biofuel capacity will be available only if there is an active refinery in the potential location f. Meanwhile, the capacity of the constructed refinery must not exceed the maximum capacity of the refinery per period and scenario. Secondly, the volume of fuel production must not exceed the refinery capacity. On the other hand, inventory capacity in each city must exist for any type of fuel in each period and scenario. Equations (9), (10), and (11) represent equilibrium constraints. Constraint (12) indicates that the purchase amount of each biomass depends on its upper bound. Equation (13) indicates the constraint, which expresses the inventory balance in demand centers. The demand for final products is a function of price, and the price of final products follows the Geometric Brownian motion. The demand function is an exponential function in which, M_{em} represents demand with price zero and $k_e \geq 0$ is the price scale function. The constraint (14) explains that each refinery only can select one type of technology. Constraints (15) and (16) indicate the connection between refineries and demand centers, as well as the connection between biomass supply chain centers and refineries. Equations (17) and (18) represent access of biomass supply centers and refineries to different types of transportation facilities.

Robustness Approach to Mathematical Model

As mentioned above, the proposed model is linear. The suggested model will be converted to a linear model due to the reasons mentioned above. Moreover, demand uncertainty is added to the mode by using robust programming and Bertsimas and Sim Approach. The index s (considered as a scenario) is added to the variables of the model to linearize it. Therefore, constraint (10) is modified based on the Bertsimas model. Hence, the proposed model serves as a linear model. This study shows that the demand parameter is a substantial parameter that its values can exceed the nominal values. Therefore, the proposed model can approach the problem's reality if this parameter is considered in uncertain conditions. As mentioned above, robust programming and Bertsimas and Sim approach are used to add demand uncertainty. The robust optimization method aims to find optimal or near-optimal solutions that are more likely justifiable. Bertsimas and Sim's approach is one of four main approaches used to consider uncertainty in robust programming. This part of the study explains this approach briefly. To do this, we consider the following linear programming model:

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(19)

$$Min \sum_j c_j x_j$$
$$s.t$$
$$Ax \le b$$

This model assumes that only right-hand coefficients have uncertain values in constraints, which is matrix A. The elements of this matrix (a_{ij}) vary in the interval $[\tilde{a}_{ij} - \hat{a}_{ij}, \tilde{a}_{ij} + \hat{a}_{ij}]$ in which $\tilde{a}_{ij}$ and $\hat{a}_{ij}$ represent nominal value and a maximum deviation of parameter a_{ij}, respectively. The proposed Bertsimas and Sim robust approaches are shown below:

(20)

$$Min \sum_j c_j x_j$$
$$s.t. \quad \sum_j \tilde{a}_{ij} x_j + z_i \Gamma_i + \sum_{j \in j_i} \mu_{ij} \le b_i \qquad \forall i$$
$$z_i + \mu_{ij} \ge \hat{a}_{ij} x_{ij} \qquad \forall i,j$$
$$z_i, \mu_{ij} \ge 0 \qquad \forall i,j$$

Where equations z_i μ_{ij} represent dual auxiliary variables and parameter Γ_i (uncertainty budget) indicates the level of conservatism, which is selected based on the importance of constraint and risk-taking level of the decision-maker.

Hence, the mathematical model robustness is done as follows:

Parameters:

$\widehat{D}_{tems}$: demand tolerance in city m and time t for biofuel e under the scenario s

Γ_{tem} : Uncertainty budget

Robustness variables:

p_{tem} and q_{tems}: variables of robust model

(21)

$$\sum_{f\in F}\sum_{k\in K} y^t{}_{efmsk} + q^t{}_{ems} + I^{t_1}{}_{ems} - I^t{}_{ems} + \Gamma_{tems} p_{tem} + q_{tems} = D^t{}_{ems}(p^t{}_{ems}) \qquad \forall e \in E, m \in M, s \in S, t \in T$$

(22)

$$p_{tem} + q_{tems} \geq \widehat{D_{ems}}^{t}({p^t}_{ems}) \quad \forall j \in J, v \in V, t \in T$$

Solution Method of Mathematical Model

The ε constrained method is one of the exact methods used for optimal a Pareto solution which was introduced by Aljedan. This method has an advantage over other multi-objective optimization methods since it can be used for non-convex solution spaces, while other methods, such as weighting combination of the objectives are not applicable in non-convex spaces. The computation time of an algorithm is a significant feature used to evaluate the algorithm. The most considerable shortcoming of exact search-based algorithms, including the ε constrained method, is their high computational time of them. Therefore, a metaheuristic algorithm can be used to reduce computational time.

The general form of an MODM problem is as follows:

(26)

$$\begin{cases} Min\ (f_1(x), f_2(x), \dots, f_n(x)) \\ x \in X \end{cases}$$

Assume that the first objective is taken into the main objective, while other objectives are constrained to the upper bound of epsilon, and then are applied to the constraints of the problem. In this case, the EC method is used and a multi-objective model (27) is formulated:

(27)

$$\begin{cases} Min\ f_1(x) \\ f_i(x) \leq e_i\ i = 2,3, \dots, n \\ x \in X \end{cases}$$

Where the first objective is considered as the main objective, while the rest objectives are constrained to the maximum value of e_i. Various solutions are obtained in model 27 by changing the e_i values, which may not be efficient (or are weakly efficient). We can solve this problem by augmenting the model (28) partially, which is known as the augmented e-constraint method (AEC) (Mavrotas, 2009). We can implement the AEC method better by measuring the suitable range of epsilons (e_i) based on lexicographic optimization (Aghaei et al., 2011). AEC method first determined the suitable range of changes in epsilons and then calculates the Pareto front based on the different values of epsilons.

1. Proper range for e_i values based on Lex method

Following optimization problems are solved for each objective $[j = 1,2, \ldots, n]$ to find the suitable range of e_i corresponding to objective i ($i = 2, \ldots, n$):

(28)

$$PayOff_{jj} = Min\, f_j(x)$$
$$x \in X$$

Where $x^{j,*}$ represents the optimal solution and $PayOff_{jj} = f_j(x^{j,*})$ indicates the optimal value of objective j. Now, the optimal value of objective j is formulated as equation (29) by considering one of $j = 1,2, \ldots, n; j \neq i$ objective as optima in each case:

(29)

$$PayOff_{ij} = Min\, f_i(x)$$
$$f_j(x) = PayOff_{jj}$$
$$x \in X$$
$$j \neq i$$

Where optimal solution $x^{i,j,*}$ with optimal value $PayOff_{jj} = f_i(x^{i,j,*})$ is calculated for objective i. Therefore, the following payoff matrix is obtained based on the Lex method.

(30)

$$PayOff = [payOff_{ij}]$$

Following terms are defined for objective $i = 1, \ldots, n$ after determining the Payoff matrix:

- $Min(f_i) = Min_j\{payOff_{ij}\} = payOff_{ii}$
- $Max(f_i) = Max_j\{payOff_{ij}\}$
- $R(f_i) = Max(f_i) - Min(f_i)$

Accordingly, the proper range is found for e_i based on the Lex method: $e_i \in [Min(f_i), Max(f_i)]$. The $R(f_i)$ value is used to normalize the objective in the AEC objective function.

2. Improving EC Method by using AEC

The model of the AEC method is formulated as equation (31) in which, the s_i value represents non-negative variables of shortage and ϕ_i indicates a parameter that is used to normalize the first objective function relative to the objective i ($\phi_i = \frac{R(f_1)}{R(f_i)}$).

(31)

$$\begin{cases} Min\, f_1(x) - \sum_{i=2}^{n} \phi_i s_i \\ f_i(x) + s_i = e_i \; i = 2,3,\ldots,n \\ x \in X \\ s_i \geq 0 \end{cases}$$

The AEC method formulated in the present study first determines the range $e_i \in [Min(f_i), Max(f_i)]$ for constrained objectives by using the Lex method. Next, the single-objective model (31) is solved afterr quantifying e_i values. This model generates an efficient solution and places the objectives' value in the Pareto front regarding this solution. Note that any change in e_i values at their corresponding ranges leads to another efficient solution and another point in the Pareto front. The next part of the study explains how AEC is used to solve the proposed two-objective model.

Validation of Mathematical Model by Using EC

Stochastic numbers are used in small dimensions to discuss and examine the proposed mathematical model, and then optimal solutions are analysed based on the indexes and parameters of the problem.

A) Introducing Dimensions of the Studies Problem

Stochastic data are used to validate the model formulated in the previous section. Each considered part is described in the table below. Hence, the model was coded in GAMS software and CPLEX solver through the EC method to evaluate and validate the proposed mathematical model. In the first section, the assumed inputs of the mathematical model are discussed and addressed:

Problem's Inputs

This step presented a pilot problem by using random data based on the papers introduced for the proposed model in the previous chapter. It should be explained that the corresponding values for the calculation of transportation costs and other input parameters of the model were evaluated by considering three types of biomasses from two different areas. Moreover, two types of transportation facilities with different capacities and an assumed refinery were taken into account. On the other hand, two demand centers, and two final products were evaluated under two Bertsimas and Sim uncertainty scenarios. According to assumptions of the problem, the fixed cost of refinery setup was 10 billion$. Furthermore, costs of maintenance and fuel shortage depended on the sales cost; 0.5% and 1% out of sales profit, respectively. The maximum capacity of the refinery equaled 100.000 million cubic liters, and the probability of scenarios equaled 0.85 and 0.15, respectively. Tables 2 to 9 indicate other parameters of the mathematical model. It is worth noting that the model was analyzed under two biomass production scenarios because the mathematical model was NP-HARD. These two scenarios were considered because the exact solution cannot evaluate more production scenarios.

Table 2. Cost of purchasing biomass

pr	I		
	1	2	3
	12	30	20

Table 3. Access of refinery to considered facility

$\boldsymbol{\lambda_{k,f}}$	T	
	1	2
	1	0
	0	1

Table 4. The capacity of stored fuel

$\mathbf{capi}_e$	M	
	1	2
	7.000	10.000
	80000	9000

Table 5. Cost of fuel production

C	E,r	
	1.1	1.2
	40	32

Table 6. Connection between biomass areas and refinery

X(I,j,f)	(t,s)			
	1.1	1.2	2.1	2.2
1.1.1	1	0	1	1
1.2.1	1	0	1	1
2.1.1	1	1	0	1
2.2.1	1	1	1	0
3.1.1	1	1	0	1
3.2.1	1	0	1	1

Table 7. Demand values for biofuel

D(e.m)	(t,s)			
	1.1	1.2	2.1	2.2
1.1	10	12	12	11
1.2.	17	17	17	23
2.1	21	12	12	20
2.2	27	19	10	22

Table 8. Fuel price in the demand center

p(e.m)	(t,s)			
	1.1	1.2	2.1	2.2
1.1	80	77	70	80
1.2.	57	70	77	50
2.1	70	77	50	57
2.2	70	77	57	50

Table 9. Cost of shipping biomass from biomass areas to the refinery

CCl(I,j)	(f,k)	
	1.1	1.2
1.1	2	7
1.2	2	7
2.1	2	7
2.2	3	7
3.1	3	7
3.2	3	7

The mathematical model was validated in GAMS software by using the AEC method. This method was used based on the inputs of the mathematical model that is described herein.

Finally, we solved the AEC by using GAMS software for obtained epsilons. Table 10 reports the set of Pareto optimal solutions.

Table 10. Optimal values of objective functions

ε	Value of the first objective function	Value of the second objective function	Value of the third objective function
1	525300	351	132
2	525450	351	135
3	525550	352	135
4	525621	355	135
5	525643	356	137

Figure 1 depicts Pareto front of the first objective function.

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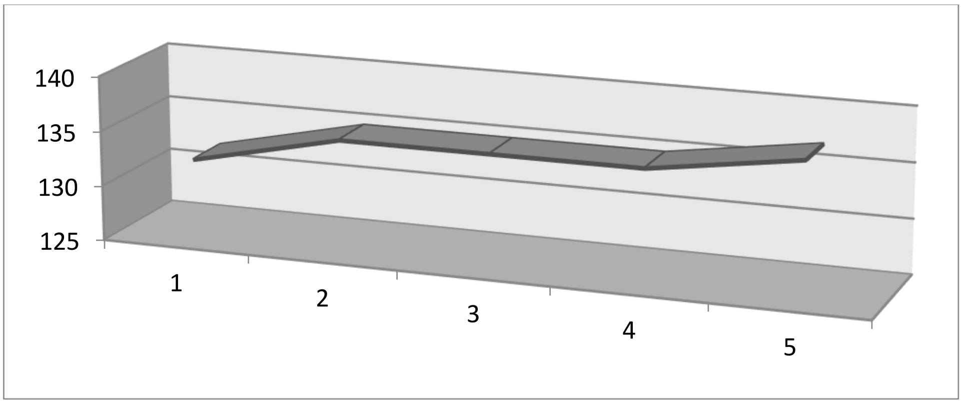

Figure 1. Pareto front of the first objective function

Figure 2 depicts Pareto front of the second objective function.

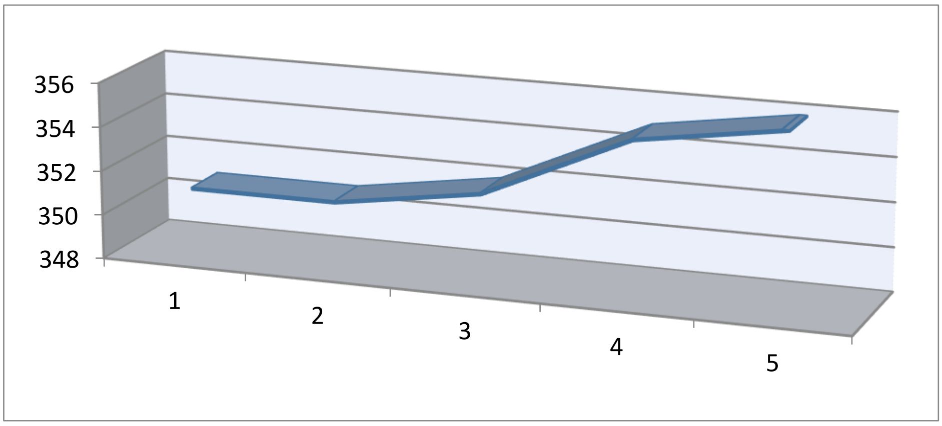

Figure 2. Pareto front of the second objective function

Figure 3 depicts Pareto front of the third objective function

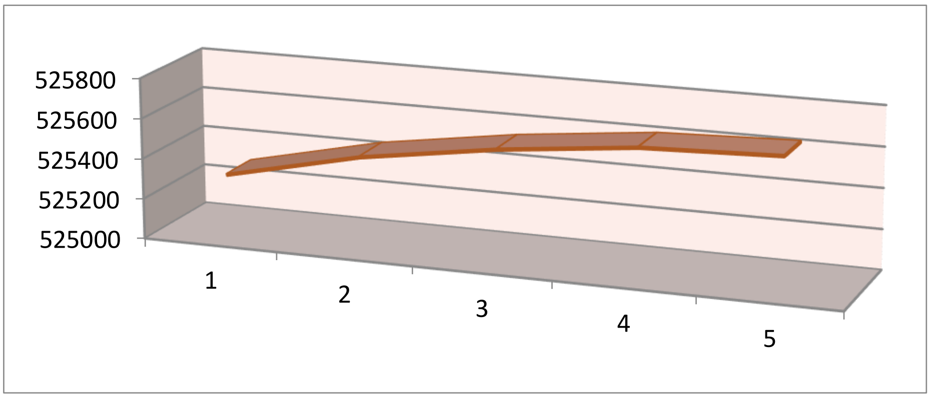

Figure 3. Pareto front of the third objective function

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Benders Decomposition Technique

Benders Decomposition Technique relies on the decomposition of a mixed-integer programming model to one master problem and one subproblem that is solved iteratively using their solutions. The subproblem includes continuous variables and corresponding constraints, while the master problem comprises integer variables and one continuous variable, which connects two problems. The optimal solution to the master problem provides a lower bound for the objective under the question. A dual is solved for the subproblem by using the solution obtained from the master problem and fixing the integer variables subproblem's input. This solution can be used to define an upper bound for the general objective of the problem. Moreover, this solution is used to generate a Bander's cut, which comprises continuous variables added to the master problem. This cut is added to the master problem in the next iteration, and then a new lower bound is found for the master problem by solving it. It is ensured that the new bound is not worsening than the current lower bound. Therefore, the master problem and subproblem are solved interpretively until reaching a termination condition, which occurs when the gap between upper and lower bounds is less than a small number. Benders Decomposition Technique obtains the optimal solution in finite iterations.

The overall problem is formulated before developing the master problems and subproblems based on Banders Technique:

(32)

$Min\ Z_p = \sum_{j\in M}\sum_{r\in R} F_j^r U_j^r + \sum_{k\in L}\sum_{h\in H} G_k^h V_k^h + BSP(x,y|U,V)$

Or to be more precise:

(33)

$$Min\ Z_p = \sum_{j\in M}\sum_{r\in R} F_j^r U_j^r + \sum_{k\in L}\sum_{h\in H} G_k^h V_k^h + BSP(x,y|\widehat{U},\widehat{V})$$

s.t:

(34)

$$\sum_{r\in R} U_j^r \leq 1 \quad \forall j \in M$$

(35)

$$\sum_{h\in H} V_k^h \leq 1 \quad \forall k \in L$$

Where $BSP(x,y|\widehat{U},\widehat{V})$ is Banders' subproblem, which consists of the following details:

Dual Subproblem

The $\mathrm{BSP}(\mathrm{x},\mathrm{y}|\widehat{\mathrm{U}},\widehat{\mathrm{V}})$ dual is used to generate Banders' cuts for the master problem. The dual variables $(\pi^1_{\mathrm{ips}},\pi^2_{ips},\pi^3_{js},\pi^4_{\mathrm{jps}},\pi^5_{\mathrm{ks}})$ are used for constraints (36), (37), (38), (39), and (40) to calculate the duality of this problem. The problem of the subproblem called $DBSP(\pi^1,\pi^2,\pi^3,\pi^4,\pi^5|\widehat{U},\widehat{V})$ is shown by consideration of these variables:

(36)

$$\max \sum_{i\in N}\sum_{p\in P}\sum_{s\in S}(-\pi^1_{ips}+\pi^2_{ips})-\sum_{j\in M}\sum_{s\in S}\left(\pi^3_{js}\sum_{r\in R}b^r_j\widehat{U}^r_j\right)-\sum_{k\in K}\sum_{s\in S}\left(\pi^5_{ks}\sum_{h\in H}e^h_k\widehat{V}^h_k\right)$$

s.t:

(37)

$$-\pi^1_{ips}+\pi^2_{ips}-a^p_i v^p\pi^3_{js}-a^p_i v^p\pi^4_{jps}\le p^s C_{ij}a_i \qquad \forall i,j,p,s$$

(38)

$$b^r_j\pi^4_{jps}-b^r_j\pi^5_{ks}\le p^s\bar{C}_{jk}b^r_j \quad \forall j,k,r,p,s$$

(39)

$$\pi^1_{ips},\pi^2_{ips},\pi^3_{js},\pi^4_{jps},\pi^5_{ks}\ge 0 \ \ \forall i,j,k,p,s$$

Banders' master problem is modeled as follows:

(40)

$$\min_{U,V} z$$

s.t:

(41)

$$z \geq \sum_{j \in M} \sum_{r \in R} F_j^r U_j^r + \sum_{k \in L} \sum_{h \in H} G_k^h V_k^h + \sum_{i \in N} \sum_{p \in P} \sum_{s \in S} \left(-\hat{\pi}_{ips}^{1k'} + \hat{\pi}_{ips}^{2k'}\right) - \sum_{j \in M} \sum_{s \in S} \left(\hat{\pi}_{js}^{3k'} \sum_{r \in R} b_j^r U_j^r\right) - \sum_{k \in K} \sum_{s \in S} \left(\hat{\pi}_{ks}^{5k'} \sum_{h \in H} e_k^h V_k^h\right) \quad \forall k' = 1, \dots, \acute{K}$$

(42)

$$\sum_{i \in N} \sum_{p \in P} \sum_{s \in S} \left(-\hat{\pi}_{ips}^{1l'} + \hat{\pi}_{ips}^{2l'}\right) - \sum_{j \in M} \sum_{s \in S} \left(\hat{\pi}_{js}^{3l'} \sum_{r \in R} b_j^r U_j^r\right) - \sum_{k \in K} \sum_{s \in S} \left(\hat{\pi}_{ks}^{5l'} \sum_{h \in H} e_k^h V_k^h\right) \leq 0 \quad \forall l' = 1, \dots, \acute{L}$$

(43)

$$\sum_{r \in R} U_j^r \leq 1 \quad \forall j \in M$$

(44)

$$\sum_{h \in H} V_k^h \leq 1 \qquad \forall k \in L$$

In this model, equation (36) represents the objective function of Banders' master problem, and equation (37) includes optima cuts that are added to the master problem after obtaining the optimal solution of the subproblem. Parameters $\hat{\pi}_{ips}^{1k'}$, $\hat{\pi}_{ips}^{2k'}$, $\hat{\pi}_{js}^{3k'}$ and $\hat{\pi}_{ks}^{5k'}$ show values of dual variables that are calculated after solving Banders' subproblem. These values are considered fixed values in cut constraints. Equation (38) includes feasibility cuts. This equation is added to the master problem if the subproblem is not feasible. Parameters $\hat{\pi}_{ips}^{1l'}$, $\hat{\pi}_{ips}^{2l'}$, $\hat{\pi}_{js}^{3l'}$ and $\hat{\pi}_{ks}^{5l'}$ represent values of dual variables that were obtained after solving Banders' subproblem. These values are considered constant values in cut constraints. General Procedure of Benders Decomposition Algorithm

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$\{\text{initialization}\}$

$(U,V) = \text{initial feasible integer solution}$

LB := -∞

UB := +∞

$L' = K' = 0$

while $(\text{UB} - \text{LB} > \varepsilon)$ Do

{solve subproblem}

if (Subproblem is Unbounded) then

Get unbounded ray π

Add cut $\sum_{i\in N}\sum_{p\in P}\sum_{s\in S}(-\hat{\pi}^{1l'}_{ips} + \hat{\pi}^{2l'}_{ips}) - \sum_{j\in M}\sum_{s\in S}\left(\hat{\pi}^{3l'}_{js}\sum_{r\in R} b^r_j U^r_j\right) - \sum_{k\in K}\sum_{s\in S}\left(\hat{\pi}^{5l'}_{ks}\sum_{h\in H} e^h_k V^h_k\right) \le 0$

to master problem

$L' := L' + 1;$

Else

Get extreme point π

Add cut $z \ge \sum_{j\in M}\sum_{r\in R} F^r_j U^r_j + \sum_{k\in L}\sum_{h\in H} G^h_k V^h_k + \sum_{i\in N}\sum_{p\in P}\sum_{s\in S}\left(-\hat{\pi}^{1k'}_{ips} + \hat{\pi}^{2k'}_{ips}\right) - \sum_{j\in M}\sum_{s\in S}\left(\hat{\pi}^{3k'}_{js}\sum_{r\in R} b^r_j U^r_j\right)$

$- \sum_{k\in K}\sum_{s\in S}\left(\hat{\pi}^{5k'}_{ks}\sum_{h\in H} e^h_k V^h_k\right)$ to master problem

$K' := K' + 1;$

UB := $\min\{\text{UB}, \sum_{j\in M}\sum_{r\in R} F^r_j U^r_j + \sum_{k\in L}\sum_{h\in H} G^h_k V^h_k + \sum_{i\in N}\sum_{p\in P}\sum_{s\in S}\left(-\hat{\pi}^{1k'}_{ips} + \hat{\pi}^{2k'}_{ips}\right) - \sum_{j\in M}\sum_{s\in S}\left(\hat{\pi}^{3k'}_{js}\sum_{r\in R} b^r_j U^r_j\right)$

$- \sum_{k\in K}\sum_{s\in S}\left(\hat{\pi}^{5k'}_{ks}\sum_{h\in H} e^h_k V^h_k\right)\}$

end if

{solve master problem}

LB := $\overline{z}$ //result of master problem

end while

This pseudocode indicates that we must find a feasible solution for the master problem at the first stage. The feasible solution is found after solving the master problem without any cut. Next, the solutions obtained by the master problem are added to the subproblem, and then the subproblem is solved. If the subproblem is not feasible and the dual solution of the subproblem is infinite, an infinite orientation is taken from the duality. This orientation is used to generate a feasibility cut, and then this cut is added to the master problem. The optimal solutions of dual subproblem are used to generate an optimal cut and add to the master problem if the subproblem is feasible and

has an optimal solution. If the resulted solution creates a better upper bound, the upper bound will be updated. Next, the master problem is resolved by using the new cut to update the lower bound. The iterative procedure continues until the gap between upper and lower bounds is less than a value.

This algorithm has been developed by using GAMS.23 software. This algorithm was implemented for the example mentioned above and outcomes were presented. As we know, the direct solution to this problem through GAMS.23 software requires 109.118 seconds. According to the results of this Table, less time is required to solve the problem by using Banders Decomposition Technique compared to the case in which, the model is solved directly based on the mixed-integer programming model. This implies the efficiency of the Banders Decomposition Technique.

Table 11 shows the lower and upper bound resulting from Banders Decomposition Technique within different iterations. Figure 4 depicts that the method reaches convergence after 17 iterations.

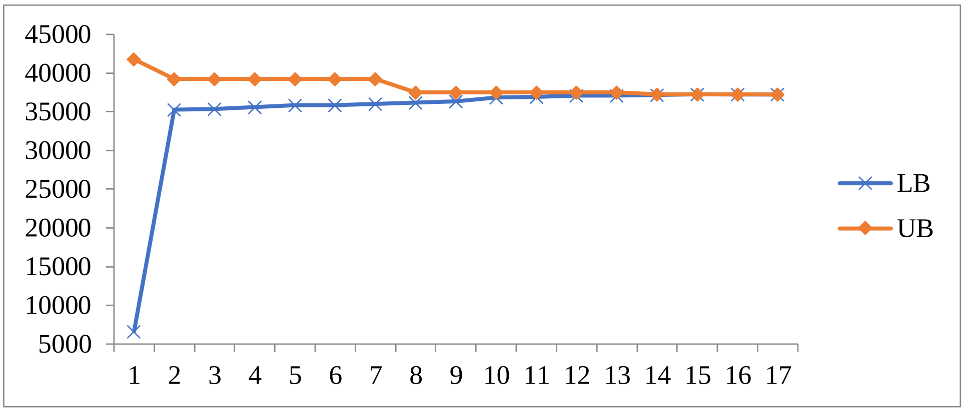

Figure 4. Convergence of Banders Decomposition Technique

Table 11. Results of numerical example solved by Banders Decomposition Technique

Model	Total variables	Total constraints	Implementation time (s)	Objective function' value
Probabilistic	286786	31758	78.698	37235.000

Evaluating performance of two EC and Banders Algorithms

Two EC and Banders Relaxation algorithms were used to evaluate solutions obtained from solving mathematical models. These two algorithms examined 12 dimensions of the problem. Therefore, this part of the study addresses the efficiency of these two algorithms in terms of the number of Pareto front of optimal solutions, quality of obtained solutions, the gap between obtained and ideal solutions, and diversity of solutions generated by EC and Banders Algorithms. The mentioned points have been reported in the Table 12.

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Table 12. Evaluating performance of two EC and Banders Algorithms

Sample	N		Q		MID		DM	
	EP	RL	EP	RL	EP	RL	EP	RL
1	8	8	0.33	0.33	0.35	0.35	0.34	0.34
2	6	6	0.40	0.40	0.38	0.38	0.37	0.37
3	5	5	0.32	0.32	0.33	0.33	0.20	0.20
4	7	7	0.97	0.97	0.80	0.80	0.72	0.72
5	5	5	0.26	0.26	0.34	0.34	0.30	0.30
6	4	4	0.07	0.07	0.05	0.05	0.04	0.04
7	9	9	0.23	0.23	0.06	0.06	0.06	0.06
8	6	6	0.49	0.49	0.40	0.40	0.38	0.38
9	4	4	0.67	0.67	0.66	0.66	0.64	0.64
10	10	10	0.07	0.07	0.01	0.01	0.01	0.01
11	9	9	0.86	0.86	0.46	0.46	0.44	0.44
12	2	2	0.05	0.05	0.73	0.73	0.70	0.70

The normality of solutions was tested by using Kolmogorov-Smirnov (K-S) test through SPSS software to implement this procedure. The corresponding tests are done by using a t-test value after determining the normality of the evaluated data. Table 13 shows K-S test results used to test the normality of solutions generated by EC and Banders Relaxation algorithms.

Table 13. One-Sample Kolmogorov-Smirnov Test

		n_epsilon	q_epsilon	MID_epsilon	DM_epsilon
N		12	12	12	12
Normal Parameters[a,b]	Mean	6.2500	0.3933	0.3808	0.3500
	Std. Deviation	2.41680	0.30407	0.25889	0.24750
Most Extreme Differences	Absolute	0.125	0.166	0.172	0.129
	Positive	0.125	0.166	0.142	0.129
	Negative	-0.122	-0.129	-0.172	-0.129
Test Statistic		0.125	0.166	0.172	0.129
Asymp. Sig. (2-tailed)		0.200[c,d]	0.200[c,d]	0.200[c,d]	0.200[c,d]

a. Test distribution is Normal.
b. Calculated from data.
c. Lilliefors Significance Correction.
d. This is a lower bound of the true significance.

According to the results of the K-S test on the EC method used to solve 12 samples, Sig. was greater than 0.05. Therefore, the data were normal.

Table 14. One-Sample Kolmogorov-Smirnov Test

		n_RL	q_RL	MID_Rl	DM_RL
N		12	12	12	12
Normal Parameters[a,b]	Mean	6.2500	0.3933	0.3808	0.3500
	Std. Deviation	2.41680	0.30407	0.25889	0.24750
Most Extreme Differences	Absolute	0.125	0.166	0.172	0.129
	Positive	0.125	0.166	0.142	0.129
	Negative	-0.122	-0.129	-0.172	-0.129
Test Statistic		0.125	0.166	0.172	0.129
Asymp. Sig. (2-tailed)		0.200[c,d]	0.200[c,d]	0.200[c,d]	0.200[c,d]

a. Test distribution is Normal.
b. Calculated from data.
c. Lilliefors Significance Correction.
d. This is a lower bound of the true significance.

According to the test analysis of NSGAII, the Sig. value was greater than 0.05. Therefore, both EC and NSGAII methods generated normal solutions. Moreover, the t-test value was used for presumptions formulated for an equal number of Pareto solutions, quality of solution, the distance from the ideal solution, and diversity of solutions.

Table 15. Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	n_epsilon	6.2500[a]	12	2.41680	0.69767
	n_RL	6.2500[a]	12	2.41680	0.69767
Pair 2	q_epsilon	0.3933[a]	12	0.30407	0.08778
	q_RL	0.3933[a]	12	0.30407	0.08778
Pair 3	MID_epsilon	0.3808[a]	12	0.25889	0.07474
	MID_Rl	0.3808[a]	12	0.25889	0.07474
Pair 4	DM_epsilon	0.3500[a]	12	0.24750	0.07145
	DM_RL	0.3500[a]	12	0.24750	0.07145

a. The correlation and t cannot be computed because the standard error of the difference is 0.

As was anticipated, EC and Banders Relaxation algorithms had the exact solution. Hence, they were identical in generating Pareto solutions, quality of solutions, the gap between generated and ideal point, and solution diversity. The reason for such similarity is that the Benders Relaxation algorithm only affects the solution time while analyzing optimal solutions as the EC algorithm does.

Conclusion and Recommendations

A biofuel supply chain involves major activities: harvesting, storing, and transporting the biomass, converting biofuel, transporting biofuel, and using biofuel. A point must be considered for preprocessing amenities and biofuel byproducts, for instance. The

warehouse must be constructed near biofuel demand locations to reduce biofuel transportation costs. Therefore, the cost of biomass transportation will be increased if the warehouse is far from the waste disposal locations. It is not possible to independently make logistic decisions, which influence the supply chain. Biofuels and corresponding production procedures are divided into three generations in classifying biomass feedstock, biofuels, and corresponding production procedures. First-generation biofuels are made from sugar and vegetable oils, which can be converted to biofuels by using conventional technologies. Most feedstocks that are used in this process can also be a food source. Therefore, the process of using food items has changed to non-edible materials. On the other hand, it is highly challenging to use this category of biofuel. Biomass production and biofuel production technology are some of these challenges. Second-generation biofuels are obtained from non-edible materials, such as lignocellulosic biomass, crops, agriculture residue, or wastes that can produce fuel. Third-generation biofuels that have been recently introduced are produced from algae. The complicated production process has prevented the commercialization of second and third-generation biofuels. The biomass flow from supply sites to demand centers is required for biofuel production. The biomass passes through some facilities in this process, which is called the biomass supply chain. Each supply chain loop requires special knowledge, technology, and activities, including growth, harvest, transportation, collection, storing, conversion, distribution, and consumption. Therefore, the present study has introduced and addressed a multi-level supply chain from supplying to distributing biofuel products. The proposed model has investigated the sustainability objectives, such as economic, social, and environmental issues of supply risk. Ultimately, the introduced model was validated by using the EC approach and then confirmed by using the integrated EC-Banders Relaxation algorithm.

Here are some recommendations based on the mathematical model formulated in the extant study:

1. Third-generation biofuels made from algae have been developed; hence, it is suggested to use them in supply chain studies for hard and soft time windows.

2. The routing and location issues can be developed in a mathematical model by considering the studied supply chain.

3. It is recommended to estimate and evaluate fuzzy logic when evaluating the costs of the mathematical model.

4. Metaheuristic algorithms have evaluation errors; hence, it is suggested to evaluate the solution time by solving the large dimensions of a mathematical model. Next, the results of solving the mathematical model can be evaluated by Banders Algorithm.

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